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A General Framework for the Statistical Analysis of Sequential Dyadic Interaction Data

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Recent interest in sequential dyadic interactions has motivated researchers to develop methods appropriate for the analysis of such data. After briefly reviewing a series of methodological papers focusing on the analysis of discrete-valued observations, we present a general framework for studying many substantive effects, including dominance and autodependencies, in social interactions measured on dyads. We show how this framework allows a researcher to study dyadic interactions measured at two or more time points on one or more relations. The methods described here are general enough to permit the simultaneous analysis of the sequential relational variables and attribute variables (such as sex of actors or emotional status of the dyad) recorded on either the dyad or the actors.

Several recent articles in *Psychological Bulletin* have described theoretical and methodological developments in the study of sequential dyadic interactions. The theoretical advances include a renewed interest in the dynamics of social interactions (Jones, 1986) and the recognition of bidirectional influences on members in the dyad. Rather than a snapshot observation of behavior, many researchers are interested in the development and change of relationships within a dyad and the effects that each member of the dyad has on the other's behavior. When the behavioral history of a dyad predicts the future behavior of the dyad, the term *serial dependence* is often used to reflect the influence that past behavior has on present or future dyad states. In earlier research, serial dependence has been viewed as a statistical difficulty, because the stochastic process that is assumed to underlie dyadic behavior yields observations that are not independent. Recently, an alternative view has emerged: The dependence between observations is of psychological interest when studying dyadic interaction data (Kenny & Judd, 1986).

One of the contexts in which the study of sequential dyadic interactions is frequently used is the analysis of coded, observational sequences of the interactions of married couples (Gottman, 1979a, 1979b, 1979c; Gottman & Bakeman, 1979; Gottman, Markman, & Notarius, 1977; Gottman & Notarius, 1978; Margolin & Wampold, 1981). Gottman and his colleagues have studied the interaction patterns in distressed and nondistressed couples and have analyzed the structure of these sequences for possible explanations of marital satisfaction. Their most important contributions to the methodology for sequential dyadic interaction data are three: (a) By concentrating on the substantive problems that can arise in marital dyads, they realized the need to collect longitudinal data and the need for statistical methods to analyze these sequential dyadic interactions; (b) they introduced statistical methods for the analysis of time-series data to many social scientists and developed some related statistical techniques (Gottman, 1981); and (c) they proposed a definition of the important notion of dyadic "dominance" (which we describe later) that many researchers have found useful.

Sequential dyadic interactions have also been examined in the study of interactions within mother–child dyads. For example, the cyclic aversive behavior interactions between mothers and their deviant children have been found to depend on mothers' attributes, such as socioeconomic status and strength of social support systems (Dumas, 1984; Dumas & Wahler, 1985). Because behaviors tend to be reciprocated (the response to negative—or positive—behavior by one member of the mother–child dyad is negative—or positive—behavior by the other member), it becomes important to understand the conditions that terminate negative or positive behavior (Martin, Maccoby, Baran, & Jacklin, 1981).

Sequential dyadic interactions are also studied within larger groups. For example, Mishler and Waxler (1975) studied triads containing mother–child and father–child dyadic interactions in both normal families and families in which the child was schizophrenic. The study of formation of coalitions of two from groups of three and the change over time of the composition of the coalition (e.g., Komorita & Chertkoff, 1973; Komorita & Meek, 1978; Komorita & Moore, 1976) is another example of studying dyads within triads. The dyad can be contained in a group larger than three, of course, facilitating the study of the relative effects of individual attributes and group characteristics on behavior (Ingraham & Wright, 1986; Wright, Giammarino, & Parad, 1986; Wright & Ingraham, 1985, 1986).

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Table 1
Four-Way Table of Hypothetical Data From Allison and Liker's (1982) Article

		W2 H2	W2 H2	W2 H2	W2 H2
W1	H1	2 2	2 1	1 2	1 1
2	2	300	79	5	16
2	1	70	11	5	14
1	2	14	5	11	70
1	1	16	5	79	300

Note. From "Analyzing Sequential Categorical Data on Dyadic Interaction: A Comment on Gottman" by P. D. Allison and J. K. Liker, 1982, *Psychological Bulletin, 91,* p. 399. Copyright 1982 by the American Psychological Association. Adapted by permission. The notation in this table represents the behavior of the husband (H) and wife (W) at times 1 (H1, W1) and 2 (H2, W2). 2 = target behavior present; 1 = target behavior absent.

The interest in theoretical and substantive issues has motivated the need to understand how to properly analyze sequential social interaction data. The examples mentioned previously should demonstrate the varied substantive applications of methodology designed for the analysis of sequential dyadic interaction data. We focus on methodological developments originating with Sackett (1979) and Gottman (1979a) and continuing with Allison and Liker (1982) and Budescu (1984) in this article. After briefly describing these methods, we present a general framework for the statistical analysis of discrete-valued dyadic interactions based on the research of Wasserman and Iacobucci (1986) and Iacobucci and Wasserman (1987). To illustrate our ideas, we adopt the substantive structure of husband–wife dyads.

The data obtained from the observation of a married couple are a string of behavioral units. The couple is usually videotaped while discussing some issue problematic to their marriage. The videotape is transcribed into coded units that measure the content of the verbal statements and perhaps the affect of the speaker or listener. The resulting data are a sequence of behaviors (a continuous record of interactions). If the recorded measurements are discrete valued (rather than continuous), they may be aggregated so that individual behaviors fall into cells of a multidimensional contingency table. Our primary focus here is on discrete-valued behaviors, primarily because the sequential analysis of continuous-valued dyadic behavior, using time-series techniques, is already well documented (mostly by Gottman, 1979c) and fairly well understood.

For example, husband–wife dyads observed at two points in time on one discrete-valued or binary-valued behavior will fall into cells of a four-dimensional contingency table. The first variable of this four-way table represents whether the husband displayed the target behavior at some time. The second margin represents the wife's behavior at that same time. The third and fourth margins represent the behavior observed for the husband and wife, respectively, at the subsequent time. For example, Table 1 contains such a 2^4 table, the hypothetical data presented and analyzed by Allison and Liker (1982, p. 399).

Review of Recent Methodology

Sackett (1979) suggested that the familiar standard normal z statistic for testing proportions be applied to sequential discrete-valued data. The proportions represent the conditional relations between different variables at different lags. For example, we might be interested in whether a wife's negative behavior (X) at time t is responded to by a husband's negative behavior (Y) at time $t + 1$. The null hypothesis would be that the occurrence of the husband's negative behavior is independent of the wife's previous behavior: $P_k(Y|X) = P(Y)$ at lag k. The numerator of the test statistic is the difference between estimates of these two probabilities: $[P_k(Y|X) - P(Y)]$. This difference is then standardized by the estimated standard error of the expected proportion (P(Y)): $[(P(Y))(1 - P(Y))/(n - k)]^{1/2}$. One then refers the observed value of the z statistic to the standard normal distribution to judge the validity of the null hypothesis.

Gottman (1979a) studied this z statistic in more detail, by focusing on estimates of conditional probabilities. Although Gottman's (1979c) main contribution to the analysis of sequential dyadic data has been the exposition of time-series methods for continuous data, he and his collaborators have also briefly described methods for discrete data. Their research is an important antecedent of the methods that we describe here. Gottman and Bakeman (1979) discussed how to compare empirical conditional and unconditional probabilities. This comparison is one way of estimating Gottman's (1979b) dominance effect.

Gottman's (1979b) definition of dominance is simply the presence of an asymmetry in the predictability of behavior. If a wife's behavior at some time is better predicted from the husband's behavior at a previous time than the reverse (predicting the husband's future behavior from the past behavior of the wife), then the husband is said to be dominant. This definition has been used by many, particularly Budescu (1984), who noted that Gottman's (1979b) definition of dominance is similar to the definition of power in dyadic relations given by Thibaut and Kelley in 1959.

Gottman and Bakeman (1979) also described the use of Markov chains to model the transitions in sequences of behavior. The data are represented in a two-way contingency table, in which the rows correspond to the different categories coded at time t and the columns correspond to the same categories for behaviors observed at time $t + 1$. For example, there may be four coded behaviors: wife or husband and complaining or agreeing (Gottman & Bakeman, 1979, p. 195). The frequency in a cell in this 4×4 table is increased by one for every pair of consecutive time periods of the behavioral sequence.

Note, however, that models for these data cannot reflect the dyadic interaction nature of these behavioral processes, because the researcher is focusing on only the husband or only the wife but not both. Dyadic interactions can be modeled by representing the sequences in a contingency table similar to the one shown in Table 1 (adapted from Allison & Liker's, 1982, Table 3), in which behaviors for both the husbands and wives are coded for times t and $t + 1$.

The suggestion made by Allison and Liker (1982) to restructure dyadic interaction data into a four-way table is, from our perspective, their most important methodological contribution. This new structure enables direct application of log-linear models that can describe sequential dyadic social interactions and can allow the researcher to test hypotheses about patterns of behavior. They also made two other major contributions. First, they corrected the estimate of the standard error of the z statistic proposed by Sackett (1979) and used by Gottman

(1979c). Second, they criticized the traditional procedures because such methods (like Sackett's statistic) do not control for autodependencies in the data. They showed that results can be quite misleading if one fails to include such effects in the analyses.

Budescu (1984) also found Allison and Liker's (1982) structure of the data useful but chose to take a different approach to the analysis of the data. He criticized Allison and Liker on three counts. First, they modeled the individual actors within a dyad, rather than the dyad itself. The actors within a given dyad are usually not independent, so the observations on the actors cannot be assumed to be a random sample from a large population of unrelated actors. Allison and Liker's methods ignored the fact that dyads, rather than actors, are sampled in studies of married couples or mother–child pairs. Budescu used the dyad as the unit of observation for these types of data (as did Iacobucci & Wasserman, 1987; Wasserman & Iacobucci, 1986; and authors of related papers).

Budescu's (1984) second criticism was that Allison and Liker (1982) postulated a common model for both individuals (or actors) in the dyad and then estimated one set of parameters for each actor. The parameters in the set were common to both actors, but their estimates were allowed to vary. Budescu argued that some effects (such as autodependence) may not be necessary for both partners, whereas other effects might be needed in the parameter set for both individuals in the dyad. For example, the behavior of actor A (e.g., the husband) at time t might be best modeled as a function of the previous behavior of actor A (himself) and actor B (his wife), but the behavior of actor B (the wife) may be solely a function of her husband's prior behavior. Both Budescu's and our models allow for this flexibility.

Third, Budescu (1984) claimed that his method is to be preferred on statistical grounds, because his methodology includes tests that can be used to identify the best fitting model. We point out that, theoretically, Allison and Liker (1982) could have also developed such tests simply by using the standard goodness-of-fit test statistics for log-linear models for multidimensional contingency tables.

Budescu (1984) adopted Allison and Liker's (1982) use of contingency tables and described the two primary approaches to the analysis of multivariate categorical data: maximum likelihood estimation of log-linear models as developed by Goodman (1964, 1968, 1970, 1971a, 1971b) and Bishop, Fienberg, and Holland (1975) and weighted least squares estimation of linear models, first presented by Grizzle, Starmer, and Koch (1969). Budescu analyzed his four-way dyadic interaction contingency tables by using Grizzle et al.'s methods, because the models and computations resemble regression and analysis of variance.

The methods that we describe rely on log-linear models. We prefer this approach over the Grizzle et al. (1969) method for three reasons. First, we believe that log-linear models are becoming fairly well-known to psychologists and that they are better understood and more frequently used by social and behavioral scientists. Furthermore, many introductions to and applications of such methods have recently been published in *Psychological Bulletin*—Bonett and Bentler, 1983; Isaac and Milligan, 1983; Olzak and Wickens, 1983; Dillon, Madden, and Kumar, 1983; Wampold, 1984; Tanner and Young, 1985; Haber, 1986; Iacobucci and Wasserman, 1987; and especially Feick & Novak, 1985—so there is substantial evidence of the growing popularity and ease of use of log-linear models for categorical data analysis.

Second, model specifications are more straightforward for log-linear models, and computer programs are considerably easier to use. The choice of a computer program is certainly a subjective decision, but it is true that Grizzle et al.'s (1969) methods require more detailed knowledge of the analysis, such as how to define the actual functions to be estimated, contrasts, design matrices, and so on. In addition, the only widely available statistics software that implements this estimation algorithm is SAS. Log-linear modeling can be done with SPSS^X, BMDP, GLIM, SYSTAT, as well as SAS.[1]

Finally, the model structure necessitated by Grizzle et al.'s (1969) use of weighted least squares as an estimation technique may not always be the most appropriate way to view categorical data. Grizzle et al. viewed such data sets as single two-way contingency tables in which the rows are populations that reflect the sampling structure of the data. A researcher may sometimes have data in which the sampling structure is either not apparent or uninteresting, motivating treating the data as if they had come from a single population. In this instance, there is only one row, and the full capacity of Grizzle et al.'s structure is not used. Furthermore, Grizzle et al. always viewed the columns of these two-way tables as responses. This implies that multivariate response variables must be made univariate, or "strung out" into a single column variable. This unnatural view can be quite confusing to the novice modeler.

Budescu (1984) described effects that might be present in the data, such as autodependencies and direct and indirect dominance, and described how his methods would be used to test for the presence of such effects. Dominance is defined as the effect of the husband or wife on future interactions in the dyad. If direct-dominance effects exist, the behavior of one member of the dyad predicts the future behavior of the other member. If indirect-dominance effects exist, the behavior of one member predicts the future joint behavior of the dyad. Budescu then classified these combinations of effects as either strong or weak dominance, but we are not interested in the labeling of the combinations of such effects.

The models that we describe shortly can include both autodependence and dominance effects, as well as many other effects that are substantively interesting. The data sets that we study are similar in structure to the four-way tables that may be analyzed by Allison and Liker's (1982) and Budescu's (1984) methods. Furthermore, the parameters contained in our models have direct counterparts in Budescu's framework because of the relation between log-linear models and logit models estimated by using Grizzle et al.'s (1969) methods.

Our framework is more general because of the theoretical approach that we take to model building. Rather than start with the data array to be analyzed, we first posit a variety of substantively meaningful models that could have generated the data. These models contain parameters that reflect important structural or longitudinal tendencies for the behavioral processes un-

[1] The computer manuals for these statistical programs discuss log-linear modeling of categorical data on the following pages: BMDP, Dixon (1983), pp. 176–201; GLIM, Payne (1985), pp. 45–53; SAS, SAS Institute (1985), pp. 184, 225–230; SPSS^X, Norusis (1985), pp. 295–365; SYSTAT, Wilkinson (1984), pp. 91–102.

der study. We then fit these models to data and determine which of the parameters are statistically significant. This approach allows the substantive models, rather than the data, to guide the researcher.

We see the framework that we describe shortly as being the next step in the evolution of methodology for sequential dyadic analysis begun by Sackett (1979) and Gottman (1979a, 1979c) and refined by Allison and Liker (1982) and Budescu (1984). Budescu's models can also be fitted by using our framework.

For completeness, we acknowledge that other methodology is indirectly related to our approach. The work of Wampold and Margolin (1982) and Wampold (1984) demonstrates that one can study sequential dyadic interactions and the presence of dominance effects by using nonparametric methods, such as runs tests and Hubert's quadratic assignment paradigm (Hubert & Baker, 1977; Hubert & Schultz, 1976; and especially Baker & Hubert, 1981). These methods are also valuable statistical tools. Dillon et al. (1983) used latent structure analysis, a technique popular with sociologists that can be applied to contingency tables of dyadic interaction data, to study dominance and lagged dependence across populations of dyads. Feick and Novak (1985) showed how to model two-way tables of frequencies of preferences made by each actor in a dyad (but not sequential preferences) by using log-linear models designed for the analysis of ordinal, categorical data.

Other researchers have proposed methods for the analysis of nonsequential social interaction data. Kraemer and Jacklin (1979) showed how to analyze univariate social interactions, and Mendoza and Graziano (1982) extended Kraemer and Jacklin's results to multivariate relations. These methods use standard multivariate statistical techniques for continuous data and, thus, may not be appropriate for discrete interaction data. Iacobucci and Wasserman (1987) showed how these methods could be modified to apply to discrete data. Also related is the social relations model proposed by Kenny (1981), LaVoie (1982), and Kenny and LaVoie (1984). This model is similar to Kraemer and Jacklin's and has been used by many researchers (see Ingraham & Wright, 1986).

An Alternative Method

Background and Data

The statistical details on the methodology we are about to describe have been presented elsewhere (Fienberg, Meyer, & Wasserman, 1985; Wasserman, 1987; Wasserman & Iacobucci, 1986), so we do not repeat those details here. Instead, we describe the models in more general terms and concentrate on the applications of these methods to sequential dyadic interaction data. We present the statistical framework in some degree of generality, but we always include models for the analysis of data such as those in Table 1 (one relation measured at two time points) as a special case. The methods that we discuss here are similar to those of Iacobucci and Wasserman (1987) but are designed for sequential, rather than cross-sectional, dyadic interaction data.

Before introducing notation, we present two reasons why this statistical framework can be considered quite general. First, the framework is general in that models may be fitted to data that include any number of relational variables and any number of time points. In addition, our models can accommodate data that describe attributes of the couple as a unit or of the individuals that compose the dyad.

Simultaneously modeling a large number of variables allows us to study a much greater number of effects or higher order interactions. We can estimate effects for autodependence at any lag and dominance at any lag. In addition, we can also estimate effects for dominance that cross over relations (e.g., if she does this at time t, he does that at time $t + 1$). We can also look for associations, or "correlations," between relations, and these effects can also depend on time or on the attributes of the actors and partners. That is, the higher order interactions between any combination of relations, time points, and attribute variables can be estimated. Because our approach to the analysis of these behavioral sequences is slightly different from those of other methodologists and because we are equipped with theory, we can ask and answer a much greater number of questions in these types of data.

The second reason that the framework may be considered general is that these models may be applied to a given sample of data that has been aggregated in several ways. No statistical method will be able to do much for data on only one couple recorded at only two time points. There are several ways to obtain replications, however, and our methods can be applied to data aggregated in any of these ways.

First, data may be aggregated over time points for one couple. This is the historical approach in the ethological, or "idiographic," tradition, in which the focus is on one couple and the time points serve as replications. In this context, the researcher must decide on the length of the sequences of behavior that will be aggregated. We cannot pretend to know how long these sequences should be: It depends on the given data and research area. We can only suggest starting conservatively—perhaps modeling sequences of, for example, five time units—and modifying the analysis on the basis of the results.

For example, if five time units were used, the series of behaviors coded at times 1, 2, 3, 4, and 5 would be aggregated with the behaviors coded at times 2, 3, 4, 5, and 6; 3, 4, 5, 6, and 7; and so on. Then interactions could be tested at lags 1, 2, 3, 4, and 5. If the only significant interactions were between (a) times t and $t + 1$ or times $t + 2$ and $t + 3$ (i.e., lag 1) and (b) times t and $t + 2$ (i.e., lag 2), then the sequences of five time units could be further aggregated to sequences of only three time units (i.e., times 1, 2, and 3; times 2, 3, and 4; times 3, 4, and 5; and so on). The subsequent analyses would be simplified, without loss of information.

Alternatively, the sequences of behaviors might be aggregated over couples, for some given number of time points. In this context, the time points are of greater interest, and the couples are serving as replications. For example, if each dyad had been analyzed separately, as described above, and most dyads showed effects at a lag no greater than one, there would be two relevant time points to model for several couples.

Two (or more) time points might also be the focus of the models when there actually were only two interesting time points during which data were collected. For example, couples might receive some score when observed at time t (e.g., during a pretherapy diagnostic session) and another score when observed at time $t + 1$ (e.g., during a posttherapy evaluation session). Whether (a) only two time points were observed or two time points were of interest in the context of all those times observed or (b) the data were aggregated to only two time points, the models would describe behavior at times t and $t+1$, for typical couples. This is the framework of Allison and Liker (1982) and Budescu (1984).

Finally, data may, of course, be aggregated over both couples and time points. Whether couples or time points serve as replications must be decided by each researcher confronted with each given data set. Sometimes this decision will be easy, as when there are few times observed but data exist for many couples. The opposite case—when the researcher had observed only one couple for a long time or for a short period at several times—would also be relatively easy.

Related issues exist in the actual coding of the behavioral sequences. For example, does one code positive, neutral, and negative affect as three levels of one relation, or does one code them as two relations—the presence or absence of positive affect and the presence or absence of negative affect. Furthermore, are time units determined by clock units, or are time units determined by the duration of thought units (as described earlier in this article). Finally, does one code a behavior for each person at each time, to allow for overlapping behavior, even when there may be dead time, perhaps necessitating a code that represents the fact that at a given time, a given person displayed none of the target behaviors. (In an example that we describe shortly, we allow for overlapping behavior.)

These issues depend on the research questions and on the available data. We cannot pretend to resolve these issues, nor would that be desirable, because, as one of our anonymous reviewers stated, "There is no right way to code social interactions." Our models may be applied to data regardless of the replication paradigm, and because we can model several relations, we can accommodate any of the coding schemes. If the researcher cannot resolve these issues on theoretical grounds, perhaps our methods could be useful in resolving these issues on empirical grounds.

We now introduce notation. Suppose that we are given sequential observations for $g/2$ husband–wife dyads on a single, binary relational variable (such as presence or absence of negative affect). There would be a pair of observations, one for each member of the dyad. We can look at this pair from the point of view of the wife as the actor and the husband as the partner, or we can look at the data from the point of view of the husband as the actor and the wife as the partner.

Because of the symmetry in the way we can treat the data, all individuals can be considered both actors and partners. An individual within a dyad will be subscripted by i as an actor and by j as a partner. For example, as actors, husband 1 would be denoted by $i = 1$, wife 1 by $i = 2$, husband 2 by $i = 3$, wife 2 by $i = 4$, and so on. As partners, husband 1 would be denoted by $j = 1$, wife 1 by $j = 2$, husband 2 by $j = 3$, and so on. The dyads that would have interacted, then, would be husband and wife 1 ($i = 1, j = 2$ and $i = 2, j = 1$) and husband and wife 2 ($i = 3, j = 4$ and $i = 4, j = 3$). The subscripts for actors and partners, i and j, range from 1 to g.

We consider the observations on these dyads at times $t, t+1, t+2, \ldots$. The Allison and Liker (1982) and Budescu (1984) data (such as those in Table 1) involve $T = 2$ time points, but we can model a general number of time points. It is common for the sequences of data to be of different lengths for different dyads, but each sequence is aggregated to pairs of behaviors at time t and $t+1$ (when looking at two time periods).

As described, data frequently are collected on a single relational variable, but occasionally, a researcher may gather more than one behavioral sequence for each dyad. For example, the verbal content codes of the dyad might be one behavioral sequence, and the nonverbal affect displayed by the dyad might be another behavioral sequence. For data such as these, the researcher will want to study the relation between the two sequences.

For a single relational variable observed at two time points, the data for some dyad (i, j) consists of bivariate quantities (k_1, l_1) and (k_2, l_2). The subscripts represent the time points during which the data were collected, whereas the ks and ls record the behaviors of the husband and wife. For example, suppose that we measure the absence (1) or presence (2) of negative affect at two points in time. If $(k_1, l_1) = (2, 2)$ and $(k_2, l_2) = (2, 1)$, then both members in the dyad display the behavior at time 1, but only the first member does at time 2.

The methods that we present can be used to analyze data more general than those in Table 1. We can extend the analyses by increasing the number of time points, the number of relational variables, or both. For example, one relational variable observed at five time points would result in the following data: (k_1, l_1), (k_2, l_2), (k_3, l_3), (k_4, l_4), and (k_5, l_5) for each dyad (i, j). Two relational variables at three time points may be denoted (again for each dyad) (k_1, l_1) and (m_1, n_1) for time t, (k_2, l_2) and (m_2, n_2) for time $t+1$, and (k_3, l_3) and (m_3, n_3) for time $t+2$.

Yet another generalization of dyadic social interaction data that can be analyzed with the models that we will present is discrete (and ordinal) data, rather than just dichotomous relational variables. Note that the data in Table 1 are frequencies of binary interactions and are aggregated over only the presence or absence of a single behavior for each husband and wife. There is no need to restrict our methods to binary data. The indicator variables k and l (and m and n and so on) can be discrete valued. For example, k and l might be binary codes for whether the individual within the dyad displayed any negative affect, but this could be generalized to discrete k and l by measuring the intensity of the negative affect displayed.

These dyadic sequential interaction data may be represented by a sociomatrix. The rows and columns of this matrix, X, are the individuals. For a specific time point and specific relation, the entries in the matrix are the value of the observed dyadic behavior (k, l). That is, for individuals i and j, there would be a k in cell (i, j) and an l in cell (j, i). There is one matrix for each time period for each relational variable, for a total of RT matrices (R = number of relational behaviors and T = number of time points).

Sociomatrices, as noted by many authors, such as Knoke and Kuklinski (1982), are helpful in representing many sorts of social interaction patterns. Many dyadic studies in psychology (such as those of husband–wife dyads) yield sociomatrices in which there is only one nonzero entry in each row and column, representing the fact that each individual interacts with only one other. Such studies focus on a small number of special dyads, because all other dyads are structurally impossible. For example, the X matrices generated by three couples measured on one binary relational variable at two time points are given in Table 2.

Table 2
Example of Sociomatrices for Three Couples, Two Time Points, and a Single Relational Variable

		X_1 (time t)						X_2 (time $t+1$)					
		$j = 1$	2	3	4	5	6	$j = 1$	2	3	4	5	6
i		H1	W1	H2	W2	H3	W3	H1	W1	H2	W2	H3	W3
1	H1	—	k					—	2				
2	W1	l	—					1	—				
3	H2			—	k					—	1		
4	W2			l	—					1	—		
5	H3					—	k					—	2
6	W3					l	—					2	—

Note. These sociomatrices contain data representing the relation between actor i and partner j. X_1 includes subscripts k (to indicate behavior from actor i to partner j) and l (to indicate behavior from partner j to actor i). X_2 includes possible values (1 and 2) that the relational variable might take. For example, in dyad 1, husband 1 (H1) reacts negatively to wife 1 (W1), who does not reciprocate the negative behavior at the same time. In dyad 2, both individuals do not behave negatively. In dyad 3, both individuals do behave negatively. All empty cells are structural zeros.

Although sociomatrices are a convenient way to represent the data, the methods that we have developed use contingency tables that are derived from the RT matrices of discrete-valued interaction data. We construct contingency tables that can be modeled by using log-linear models of the dyadic probabilities. Our approach, as noted by Wasserman and Iacobucci (1986), allows these models to be fitted by using any log-linear, categorical-data-modeling computer program.

We define a multidimensional Y array, in which the margins are subscripted by using the notation described above. For a dyad observed at two time periods ($T = 2$) on a single relational variable ($R = 1$),

$$Y_{ijk_1l_1k_2l_2} = 1 \text{ if the dyad } (i, j) \text{ behaved as described by } (k_1, l_1) \text{ at time 1 and by } (k_2, l_2) \text{ at time 2 and}$$
$$= 0 \text{ otherwise.}$$

Note that there is no restriction that the ks or ls be binary (see Wasserman & Iacobucci's, 1986, article).

A Y array may be constructed for any of the data-gathering scenarios that we have described. Consider the following four cases, which are distinguishable on the basis of the number of observed time points and the number of relations. The nonzero elements in the Y arrays would be in the following cells:

1. Single relation and two time points,
$$Y_{ijk_1l_1k_2l_2} = 1 \quad \text{for dyad } (i, j).$$
2. Single relation and T time points,
$$Y_{ijk_1l_1k_2l_2\cdots k_Tl_T} = 1 \quad \text{for dyad } (i, j).$$
3. R relations and two time points,
$$Y_{ijk_1l_1k_2l_2m_1n_1m_2n_2\cdots y_1z_1y_2z_2} = 1 \quad \text{for dyad } (i, j).$$
4. R relations and T time points,
$$Y_{ijk_1l_1k_2l_2\cdots k_Tl_T\cdots y_1z_1\cdots y_Tz_T} = 1 \quad \text{for dyad } (i, j).$$

The number of dimensions for each of these Y arrays is 6, $2T + 2$, $2R + 2$, and $2RT + 2$, respectively. The first two dimensions of these Y arrays always refer to the actor pair. It should be clear that the methods that we use are adaptable to a wide variety of data. Furthermore, as the data become richer, the estimable parameters, which we describe shortly, become more interesting.

Attribute Variables

Before discussing the models and parameters, we describe another way in which the methods that we use can be generalized. The Y array is built on the data of individuals, yet we are seldom actually interested in the behavior of particular individuals or particular dyads. Instead, the interest is usually focused on how actor subgroupings defined by an attribute characteristic of the individuals or the dyad interact with the observed behaviors.

For example, the attribute variable "distressed versus nondistressed" is usually considered a characteristic of the couple. That is, a clinician classifies the couple on the basis of scores on marital satisfaction inventories or on the basis of help sought. Then, the data on distressed couples could be compared with data on nondistressed couples. Dyadic attributes can be viewed as stratifying variables that place dyads into a finite number of strata or populations.

In addition, there is frequently demographic information on the individuals within the couple. For example, the attribute of sex is usually used when studying married couples, so that each actor is placed into a category defined by his or her sex. Such is the case in Table 1, although in this situation, same-sex interactions do not occur. For other examples, the ages of the husbands or wives might be a contributing factor to the satisfaction obtained in the relationship, or distress could be an attribute variable measured at the level of the individual if it was, say, a score on an attitude questionnaire that could be used to place the husbands and wives separately into categories on the basis of their individual opinions regarding the satisfaction of the marriage.

It should be clear that there are two types of attribute variables. One type consists of dyadic attributes that are recorded on dyads (so that the actors in a dyad have identical values on the attribute). The other type consists of actor attributes that are measured on individual actors (and may mean that a dyad contains actors with differing values on the attribute).

Table 3
Six-Dimensional W Array Corresponding to Data in Table 1

			$s = 1$				$s = 2$			
			$l_1 = 1$		$l_1 = 2$		$l_1 = 1$		$l_1 = 2$	
r	k_1	k_2	$l_2 = 1$	$l_2 = 2$	$l_2 = 1$	$l_2 = 2$	$l_2 = 1$	$l_2 = 2$	$l_2 = 1$	$l_2 = 2$
1	1	1	0	0	0	0	300	5	14	11
		2	0	0	0	0	79	16	5	70
	2	1	0	0	0	0	70	5	16	79
		2	0	0	0	0	11	14	5	300
2	1	1	300	79	70	11	0	0	0	0
		2	5	16	5	14	0	0	0	0
	2	1	14	5	16	5	0	0	0	0
		2	11	70	79	300	0	0	0	0

Note. r = actor subgroup; s = partner subgroup; k_1 and k_2 = behavior observed for the actor at times 1 and 2 (or times t and $t + 1$), respectively; l_1 and l_2 = behavior observed for the partner at times 1 and 2 (or times t and $t + 1$), respectively.

To demonstrate how to include attribute variables in a sequential dyadic data analysis, we start with data for $g/2$ couples on a single relational variable at two time points. To make things concrete, we again have married couples and both a dyadic attribute and an actor attribute: whether or not the couple has been classified as distressed and the age of the actor (categorized into a finite number of classes). Thus, dyad (i, j) falls into one of two categories, for which we use the superscript d; individual i falls into age group r; and individual j falls into age group s. (We have chosen to use just one attribute variable for the dyad and one for the individuals to keep things simple.) We then modify the Y array to incorporate these attribute variables as follows.

A W array contains the information in the Y array but focuses on the subgroups d, r, and s. A W array is defined by the attribute variables and is formed by summing the Y array over the appropriate dyads and individuals. That is, a typical entry in this array, $W^{(drs)}{}_{k_1l_1k_2l_2}$ is the sum over the $(i, j, k_1, l_1, k_2, l_2)$ cells of Y where $i \in r$, $j \in s$, and $(i, j) \in d$. If one has A_1 dyad attribute variables, then the first A_1 dimensions of the W array correspond to these variables. If one also has A_2 actor attribute variables, then the next $2A_2$ dimensions of the array correspond to these variables (because one must record the variable values for both the sending and receiving actors in the dyad). Rather than model the Y array, the researcher interested in subgroup differences would model the W array. More detail on incorporating attribute variables into the analysis of nonsequential social network data and dyadic interaction data can be found in Wasserman and Galaskiewicz's (1984) article and Fienberg et al.'s (1985) article.

Once again, the framework is adaptable; a researcher might have attribute variables on the dyads and individuals, on just the dyads or the individuals, or on neither the dyads nor the individuals. Note that the data in Table 1 represent part of a W array incorporating a single actor attribute variable (sex). The full six-dimensional W array, which contains the four dimensional array in Table 1, is given in Table 3.

As can be seen, the array in Table 1 is the northeast quadrant of the array in Table 3, because the northwest and southeast quadrants, giving husband–husband and wife–wife interactions, are structurally zero in studies of married couples. The southwest quadrant is a transposition of the northeast quadrant. That is, the g individual actors (husbands and wives) serve both as sending actors (those performing the target behavior) and as receiving actors (those witnessing the target behavior).

For example, husband i displays negative behavior (e.g., criticizes his spouse) with intensity k, and wife j displays the negative behavior (criticizes her spouse) with intensity l. Viewing the data (k, l) for dyad (i, j) is the same as viewing the data (l, k) for dyad (j, i).

Sometimes, one is interested only in the behavior sequences and not actor or dyadic characteristics. If the W array is collapsed over these variables, one loses all information about the individual actors and dyads. The resulting contingency table, which is termed a *V array,* represents only the relational variables and time points. A typical entry is $V_{k_1l_1k_2l_2}$, which gives the number of dyads with value (k_1, l_1) on the behavior at the first time and (k_2, l_2) on the second behavior. The V array derived from the data in Table 1 by collapsing over the sex of the actors in the dyad is given in Table 4. The methods of Gottman (1979a, 1979c), Allison and Liker (1982), and Budescu (1984) are applicable only to parts of the W array that contain information on a single binary actor attribute variable from one of the four possible quadrants of the table (i.e., these authors analyzed only tables such as Table 1). We consider both V and complete W arrays with arbitrary numbers of attribute variables. We present models applicable to data sets containing attribute information on the dyads, the individuals, or both because we believe this is most frequently the case.

Models

Before we describe how to fit models to Y, W, and V contingency tables, it would be useful to review the notation that we use to represent parameters and the margins of the table that correspond to the associated sufficient statistics. This notation comes from Fienberg (1981). A set of numbers in brackets implies that the model includes parameters for the highest order interaction between the margins listed, as well as all lower order effects. For example, [124] represents fitting the 124 interaction; the 12, 14, and 24 two-factor interactions; and the main effects for margins 1, 2, and 4.

Table 4
V Array Formed by Collapsing Over Attribute Variable (Sex) in Table 3

		$l_1 = 1$		$l_1 = 2$	
k_1	k_2	$l_2 = 1$	$l_2 = 2$	$l_2 = 1$	$l_2 = 2$
1	1	600	84	84	22
	2	84	32	10	84
2		84	10	32	84
		22	84	84	600

Note. k_1 and k_2 = actor behavior at times 1 and 2 (or times t and $t + 1$), respectively; l_1 and l_2 = partner behavior at times 1 and 2. These four take on the value 1 when the behavior did not occur and the value 2 when the behavior did occur.

The margin numbers correspond to the subscripts and superscripts in the W or V arrays. For example, for the data array $W^{(drs)}{}_{k_1l_1k_2l_2}$—which incorporates a single attribute variable for both the dyad (d) and the individuals (r and s), two time points, and one relational variable—the notation [1] [2] [3] [4] [5] [6] [7] implies that the log-linear model contains main effects only for the variables corresponding to the subscripts d, r, s, k_1, l_1, k_2, and l_2, respectively.

An example might be useful. Fitting the log-linear model [4] [5] [6] [7] would be equivalent to collapsing over dyads and individuals (i.e., modeling the V array) and fitting only the main effects on the relational variables (variables 4–7). This model assumes independence between individuals at a given time; that is, no parameters correspond to the [45] or [67] margins. It also assumes independence between time points, because there are no terms in which [4] or [5] interacts with [6] or [7], such as [46] = [57] (an autodependence effect) or [456] = [457] (the interaction specifying an association between the behavior of both dyad members at time 1 and the behavior of one member of the dyad at time 2).

To start simply, we describe models that may be fit to a V array for two time points and a single relational variable with no attribute variables. An example of such an array is given in Table 4. Such a table is four-dimensional, and a typical entry, $V_{k_1l_1k_2l_2}$, represents the number of dyads in which one actor displays the target behavior at rate k_1 during time 1 and k_2 during time 2 and the other actor displays it at rates l_1 and l_2.

In a four-way contingency table, there are four margins corresponding to main effects, six margins for two-factor interactions, four for three-factor interactions, and a single margin for the four-way interaction. Because we know the psychological meaning associated with each margin (e.g., variable 4—subscripted with l_2—is the behavior of an actor at time 2), we can fit a log-linear model that contains specific interactions and test any parameter that seems interesting.

Some examples of effects that may be interesting follow. If there were no time effect, the model [12] [34] would fit, because this model has no interactions between behaviors at time 1 and time 2. The effects corresponding to the [12] margin are associated with behavior at time 1, and the effects corresponding to the [34] margin are associated with behavior at time 2. If there was, in fact, an effect of carryover from time 1 to time 2, we would need parameters that indicated an interaction between time 1 ([1] and [2]) and time 2 ([3] and [4]), such as [13] [24], [123] [124], or [23] [14].

An example of an interaction between the two time points is the parameters associated with the [13] = [24] margins, which can be interpreted as autodependence effects for actors who (continuing with the earlier scenario) are either criticizing or being criticized. The parameters associated with the [23] = [14] margins correspond to a dominance effect between the behavior of one actor at time 1 and that of the other actor at time 2. The [123] = [124] margins are associated with effects for the entire dyadic behavior at time 1 interacting with the behavior of just one of the actors at time 2.

Now consider a six-dimensional W array that incorporates a single actor attribute variable (such as sex). Refer again to Table 3. The main effects might be interesting if the overall behavior levels differ between time points (variables 3 and 4, whose margins are equal by symmetry, vs. variables 5 and 6, which are also equal by symmetry). Included in Table 5 is a list of possible interpretations of some of the higher order effects for this six-way W array. Models that fit the data could include any hierarchical subset of these effects.

A model such as [12345] [12346] would be interpreted as follows: "Conditional on the dyad's behavior at time 1 ([34]) and the sex of the actors ([12]), the behaviors of the husband and wife at time 2 ([5] and [6]) are independent of each other." Or perhaps the model that best fits the data is [1235] [1246]. This model suggests that the behaviors of the husband and wife (conditional on the sex of the actors) are not affecting each other but that the only important effects are autodependencies of time 1 behavior on time 2 behavior.

Two more sets of effects are often central to the study of husband–wife dyads. These are direct and indirect dominance—the predictability of a person's or the dyad's behavior at some time by the other person's behavior at the previous time. Parameters measuring the effect of a dominant husband or wife could be included in the model by fitting the margins [1245] = [1236]. The model [1245] [1236] lacks autodependence effects, which

Table 5
Interpretations of Some Margins in the Six-Dimensional W Array: $W = \{W^{(rs)}{}_{k_1l_1k_2l_2}\}$ (With Criticism as the Single Behavior)

Margin	Interpretation of associated parameters
[12]	Sampling structure of W array
[13] = [24]	Actors criticizing at time 1
[16] = [25]	Actors being criticized at time 2
[34]	Reciprocal criticism at time 1
[35] = [46]	Overall autodependence effect for all actors
[36] = [45]	Overall direct dominance (actor criticizing at time 1 and gets criticized at time 2)
[135] = [246]	Autodependence effect dependent on type of actor (i.e., [35] = [46] depends on subgroups)
[356] = [456]	Overall indirect dominance (behavior of actor at time 1 interacts with behavior of dyad at time 2)
[1356] = [2456]	Indirect dominance differing by subgroups
[3456]	Dyadic interaction at time 1 interacts with same at time 2

Table 6
Interpretations of Some Margins in the Seven-Dimensional W Array: $W = \{W^{(drs)}_{k_1l_1k_2l_2}\}$

Margin	Interpretation of associated parameters
[123]	Sampling structure of W
[45]	Reciprocal behavior at time 1
[145]	Reciprocal behavior at time 1 dependent on type of dyad
[2345]	Reciprocal behavior at time 1 depends on attributes of individuals within dyad
[12345]	Reciprocal behavior at time 1 depends on attributes of dyad and individuals
[46] = [57]	Autodependence effect
[47] = [56]	Direct-dominance effect
[147] = [256]	Direct dominance depending on type of dyad

suggests that within-actor behavior is changing over time; that is, there is no sequential dependence of an actor's time 2 behavior on his or her behavior at time 1. Incorporating autodependencies with dominance would mean fitting the margins [35] [46] [36] [45]. Allowing these effects to depend on attribute variables would mean fitting [1235] [1246] [1236] [1245] in the model. Indirect dominance, as Budescu (1984) defined it, is the effect on both actors in the dyad of an individual actor's previous behavior, so indirect dominance on the part of the husband or wife would be reflected in the parameters associated with the margins [12356] = [12456].

As the data become richer, more variables are measured, and the associated W and V arrays grow in size. Consequently, these arrays have larger numbers of margins that are sufficient statistics for various effects and more complex and interesting parameters. It should be clear that W arrays, unlike V arrays, allow the researcher to postulate that any effect for time or the relational variables can depend on the attributes of the actors and dyads. For example, the autodependence effect for distressed couples might be nearly zero, suggesting inconsistent or changing behavior, whereas the autodependence effect for nondistressed couples might be nonzero. If we use just this single dyadic attribute and measure a single relation at two time points, then the five-dimensional array $W = \{W^{(d)}_{k_1l_1k_2l_2}\}$ would be modeled with a log-linear model containing parameters corresponding to the interaction [124] = [135]. That is, the overall autodependence effect ([24] = [35]) would depend on the type of couple (d, denoted by variable 1).

We list interpretations for some of the higher order margins of a seven-dimensional W array—formed from a dyadic attribute, an actor attribute, and one relation measured at two time points—in Table 6. Once again, the models that fit the data might include any hierarchical subset of these margins. One should always include the [123] margin in all models under consideration for this W array. This three-dimensional margin corresponds to the attribute variables for the dyad and individuals. This margin is usually considered fixed by the sampling design, so one should always statistically condition on the numbers of actors and dyads that fall into the cells of this three-way margin.

We include two more tables that are lists of interpretations of margins for other data arrays. Table 7 contains a list of the effects for an 8-dimensional V array, with entries $\{V_{k_1l_1k_2l_2k_3l_3k_4l_4}\}$ (i.e., one relational variable extended to four

Table 7
Interpretation of Margins in the Eight-Dimensional V Array: $V = \{V_{k_1l_1k_2l_2k_3l_3k_4l_4}\}$

Margin	Interpretation of parameters
[13] = [24], [25] = [36], [37] = [48]	First-order autodependencies
[15] = [26], [27] = [38]	Lag 2 autodependence effects
[12], [34], [56], [78]	Reciprocal behavior at each time
[1278]	Reciprocal behavior at time 1 interacting with reciprocal behavior at time 4
[347]	Reciprocal behavior at time 2 interacting with individual's behavior at time 4

time periods and no attribute variables). Table 8 contains a list of effects for models of an 11-dimensional W array, with entries $\{W^{(drs)}_{k_1l_1k_2l_2m_1n_2m_2n_2}\}$ (attribute variables for the dyad and individuals, two time periods, and two relational variables).

These data arrays are only three examples of the many types of data that can be analyzed by using this general framework. A researcher can have more than one (binary, discrete, or ordinal) relational variable and more than two time points and can also incorporate actor and dyad characteristics into the models. The general approach taken here to sequential dyadic interaction data uses common sets of parameters and is easily applied to any type of data set. As we have stated earlier, the effects that we have discussed have their counterparts in other approaches. The theoretical basis of our framework, however, allowed us to easily generate the lists of effects and associated margins that must be fitted. Most of these effects had not yet been studied or even identified.

The effects are straightforward to understand, and they are easy to generate: One needs only to remember which margin or subscript belongs to which variable or time point. The parameters associated with the effects are also easy to test. The logic of the parameter testing follows the standard log-linear approach: The fits of two models, one of which contains the parameters in question and one of which does not, are compared. These tests are simply conditional likelihood ratio tests, in the spirit of hierarchical model fitting, and use the standard likelihood ratio test statistic. For example, in testing whether the parameters associated with the interaction [234] are zero, one might compare the fit and degrees of freedom of a model like [123] [124] [134] [234] with the model [123] [124] [134]. The theory of these tests is explained in many sources, including Fienberg's (1981) book and Bonett and Bentler's (1983) article.

The likelihood ratio test statistics should be calculated by us-

Table 8
Interpretation of Margins in the 11-Dimensional W Array: $W = \{W^{(drs)}_{k_1l_1k_2l_2m_1n_1m_2n_2}\}$

Margin	Interpretation of associated parameters
[123]	Sampling structure of W
[48] = [59]	"Correlation" of relations at time 1
[6, 10] = [7, 11]	"Correlation" of relations at time 2
[456789]	Dyadic interaction of relations 1 and 2 at time 1 with relation 1 at time 2

Table 9
W Array for Hypothetical Data on 5- and 7-Year-Olds Conversing

			$s = 1$				$s = 2$			
			$l_1 = 1$		$l_1 = 2$		$l_1 = 1$		$l_1 = 2$	
r	k_1	k_2	$l_2 = 1$	$l_2 = 2$	$l_2 = 1$	$l_2 = 2$	$l_2 = 1$	$l_2 = 2$	$l_2 = 1$	$l_2 = 2$
1	1	1	2	2	2	2	0	2	2	0
		2	2	2	2	2	0	2	2	0
	2	1	2	2	2	2	0	2	2	0
		2	2	2	2	2	0	2	2	0
2	1	1	0	0	0	0	0	0	0	0
		2	2	2	2	2	0	0	16	0
	2	1	2	2	2	2	0	16	0	0
		2	0	0	0	0	0	0	0	0

Note. $r = 1$ represents 5-year olds as actors; $s = 1$ represents 5-year olds as partners; $r = 2$ represents 7-year olds as actors; $s = 2$ represents 7-year olds as partners; (k_1, l_1) represents talking behavior of dyad at time 1, where 1 represents no talking and 2 represents presence of talking by that actor; and (k_2, l_2) represents talking behavior of dyad at time 2.

ing the Y arrays, rather than the W or V arrays that are used to fit models. The reason behind this calculation is that the basic unit in our modeling is the dyad, so one must compare estimated probabilities for the dyads based on some model with the dyad values actually observed. Thus, if one does not model the entries in the Y array, statistics generated by "canned" log-linear modeling procedures will be incorrect.

Examples and Conclusion

Budescu (1984) analyzed Allison and Liker's (1982) hypothetical data (shown in Table 1) as a four-way contingency table, so we do not reanalyze these data. For these data, Budescu found that a wife's behavior at time t is a function of her previous behavior and her husband's previous behavior, whereas the husband's behavior may be adequately modeled solely as a function of his wife's previous behavior (i.e., the wife is directly dominant). Finally, the couple's joint behavior is independent of the dyad's previous interactions.

We chose to construct and analyze an example of a full W array. The scenario is identical to the data studied by LaVoie (1982). Boys 5 and 7 years old are paired and allowed to interact. Thus, the Y array, giving the recorded interactions among the pairs, is aggregated over age to produce four groups of 5- and 7-year-old boys: 5-year-olds with 5-year-olds, 7-year-olds with 7-year-olds, and mixed age pairs. Note how these data are more complete than mixed sex couples. All subgroups are allowed to interact. There are no husband–husband or wife–wife interactions in studies of married couples, but in this example, there are 5-year-olds playing with other 5-year-olds and 7-year-olds playing with other 7-year-olds. If we had data for 5- and 7-year-old girls as well, the W array would be structured to include sex as a subgroup variable.

We consider one relational variable at two time points to be consistent with our introduction of these methods. We suppose the relational variable to be whether a child is recorded as talking during the given time interval. When two 5-year-olds are paired in their play, we might expect some random talking, whereas the talking behavior of two 7-year-olds might resemble turn-taking conversation. (The actual age at which this behavior of taking turns is acquired is not important for our example.)

The W array created with the expected structure is found in Table 9. The hypothesized randomness of the 5-year-old-children pairs is simulated by an entry in every possible combination of behavior at times 1 and 2. The turn taking of the 7-year-old pairs is simulated by entries only in the cells that correspond to one person talking at one time and the other person talking at the other time, that is, $(k_1, l_1) = (2, 1)$ and $(k_2, l_2) = (1, 2)$ or $(k_1, l_1) = (1, 2)$ and $(k_2, l_2) = (2, 1)$. Finally, the 5- and 7-year-old mixed pairs are somewhere in between. The 5-year-old behaves somewhat randomly by talking or not talking without regard to current or past behavior of the 7-year-old. The 7-year-old modifies his own behavior as a result of the current or past behavior

Table 10
Models and Statistics for Hypothetical Data on 5- and 7-Year-Olds Conversing

Model	ΔG^2	Model tested against	p
A. [12] [34] [56] [13] [24] [15] [26] [14] [23] [16] [25]			
B. [12] [34] [56] [13] [24] [15] [26] [14] [23]	0	A	1.000
C. [12] [34] [56] [13] [24] [15] [26] [16] [25]	0	A	1.000
D. [12] [34] [56] [13] [24] [14] [23] [16] [25]	0	A	1.000
E. [12] [34] [56] [15] [26] [14] [23] [16] [25]	0	A	1.000
F. Model A + [35] [46]	1.244	H	.265
G. Model A + [36] [45]	14.434	H	.000
H. Model A + [35] [46] [36] [45]			
I. Model H + [345] [346]	0	H	1.000
J. Model H + [356] [456]	0	H	1.000
K. Model H + [134] [234]	9.617	H	.002
L. Model H + [156] [256]	9.617	H	.002
M. Model H + [135] [246]	41.023	H	.000
N. Model H + [136] [245]	11.742	H	.001
O. Model H + [145] [236]	11.742	H	.001
P. Model H + [146] [235]	3.551	H	.060

Note. All these ΔG^2 statistics have 1 degree of freedom.

of the 5-year-old. This implies that the 7-year-old does not talk while the 5-year-old is talking.

We fitted a variety of models to the data arranged in the six-dimensional *W* array of Table 9. The models and their fit statistics are included in Table 10. Table 5 gives the substantive meanings of the fitted parameters and associated margins (substitute the words *talks to* for the word *criticizes*). Before describing the parameters that were significant, we repeat that the statistical tests are hierarchical. Two models are fitted; one model includes the parameter of interest, the other does not, and the fit statistics for these two models are compared. The models whose fit statistics were compared are also listed in Table 10.

The structure that we have built into these data is reflected by the parameters that are significant. The largest effect corresponds to the [135] = [246] margins, which represent the subgroup, or age-related, autodependence. That is, for this example, these statistically important parameters reflect the fact that 5-year-old but not 7-year-old actors talk at both time 1 and time 2.

Two more sets of parameters were important in the models that we fitted to these data. The first set was that corresponding to the margins [36] = [45], [136] = [245], and [145] = [236]. The simpler effect ([36] = [45]) represents the dominance of the relational behavior. For this example, dominance is simply turn taking: One child talks at one time, and the other child talks at the next time. The other, more complicated effects involve the attribute variables and indicate that this behavior again depends on the subgroup, or the age of the children in the dyad.

The second set of important parameters corresponds to effects for margins [134] = [234] and [156] = [256]. The parameters associated with [34] imply mutual, or reciprocal, talking at time 1, and those associated with [56] imply mutual talking at time 2. The fact that the parameters associated with the margins given above are statistically important implies that this mutual talking effect at time 1 and at time 2 depends on the age of the children. This is exactly as it should be, given how we constructed the data.

This example illustrates some of the generality of the statistical framework that we have described. The effects that Gottman (1979a, 1979c), Allison and Liker (1982), and Budescu (1984) were interested in may all be estimated within this framework. Furthermore, we have shown that by using the techniques that we have described, many more types of (discrete) data may be analyzed, and many more types of effects may be estimated. We have emphasized the applicability of the models rather than the statistical details, but we remind the reader that these details exist in other articles (Fienberg et al., 1985; Wasserman, 1987; Wasserman & Galaskiewicz, 1984).

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